Managing renewable energy production risk

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ABSTRACT

The growing share of renewables paired with their intermittent nature introduces significant new challenges for market participants along the value-chain in power markets. Taking the view of an owner of such a physical renewable asset we showcase the management of the associated stochastic production risks in Germany, one of the most dynamic electricity markets and the largest producer of renewable energy in the EU-28. We find that unhedged renewable portfolios are very risky and existing vanilla derivatives are poor hedges. New exotic quantity-related weather contracts proposed by major energy exchanges (EEX) show a lot of potential but are still very illiquid. Their hedging performance is heavily driven by the market wide renewable generation portfolio which, in its current state, favors specific regions. In the long-run price-related derivatives will transform into more useful hedging instruments due to the growing importance of renewables in the formation of wholesale market prices.

1. Introduction

Global electricity generation from renewables is on the rise with investments into green technology steadily growing and even surpassing those of conventional electricity generation assets such as fossil fuel-powered power plants (EIA, 2016). However, renewable energy projects are usually associated with a considerable amount of risks plaguing potential investors. With some countries starting to scale back their subsidy mechanisms, several studies already predict the possibility of a funding gap for investments into renewable technology. Obviously, this might endanger the ambitious emission reduction targets set by European countries such as Germany (e.g., Economist-Intelligence-Unit, 2011; Bundesnetzagentur, 2015).

Currently, in Germany the most important contributors to green energy are wind and solar generators with both roughly 40 GW of installed capacity (Bundeskartellamt, 2016). Renewables already come close to satisfying market-wide electricity demand without the need of conventional power if weather conditions are favor-able. However, the intermittent nature of wind and solar power poses severe challenges for owners of such generation technology. Adverse weather conditions can result in significant drops in the amount of electricity produced, which might negatively affect revenues from selling the commodity in the marketplace. Indeed, as the renewables' share of electricity generation has increased, so have the financial consequences of risks associated with the renewables' intermittent nature. In principle, these risks affect all the players within electricity markets but the players' opportunities to mitigate risk clearly differ. While large utilities might be able to mitigate a major part of their risk simply through diversification, smaller power producers in the renewable sector, such as wind park or solar farm operators, need alternative solutions to cope with their highly uncertain revenues due to weather-related risks being potentially very specific to their location. Customized OTC products, presumably at a high cost, are one possibility. Standardized exchange-traded products could be an alternative.

Unfortunately, our understanding of how available financial derivatives perform in mitigating renewable energy risk is very limited. To the best of our knowledge, no previous work has studied whether standardized exchange-traded products are viable tools to hedge renewable energy risk. Such an assessment is challenging for at least two reasons: First, the dramatic growth in renewable generation has changed the characteristics of wholesale

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electricity prices considerably over the last couple of years and this transformation will continue in the future. The share of electricity generated from renewable energy sources steadily increases and generation varies stochastically leading to a sizable decrease in the average price level. Nevertheless, it is notoriously difficult to judge how changes in renewable generation capacities affect other characteristics of market prices although some recent studies have shown that renewables tend to have an increasing impact on price volatility (Ketterer, 2014). Second, recent amendments in the subsidy scheme ("EEG2012"), compensating renewable electricity generation, have made alterations to the existing fixed price scheme aiming at a more market-oriented compensation. This is supposed to be achieved by linking subsidies to technology-specific whole-sale market prices.[1] Both of these challenges call for an understanding of the link between wholesale market prices and local renewable generation from different technologies. Such an understanding is complicated by the fact that we have only a few years of publicly available data of market-wide renewable production at hand and there generally is a considerable lack of information with regard to local generation.

In this study, we assess how much risk renewable energy producers can hedge through financial risk transfer with exchange-traded derivatives. To answer this question we make use of an electricity price model capable of taking into account the distinct impact of weather-dependent renewable generation as well as the spatial distribution of renewable generation capacities proposed in Hain et al. (2017). This allows us to quantify location-specific weather-related risks in a meaningful way and to investigate how effective exchange-traded futures are in hedging production risk of wind and solar parks at different locations in Germany. Since the renewable generation portfolio is in constant change, we also assess how portfolio alterations affect hedging effectiveness on the short- and long-run.

We have opted for the German power market specifically due to the country's leading role as a promoter of green electricity. Germany was one of the first countries that introduced a subsidy scheme aimed at fostering investments into renewable electricity production in the mid90's and has since then grown to the leader of power generation out of renewable energy sources among large industrial nations (Bloomberg, 2016).[2] About 27% of its electricity in 2015 was produced purely from renewable power plants which is about three times the amount of the level a decade ago and roughly double of what the United States produced. Furthermore, Germany is still among the top 5 (top 10) countries with regard to investments into wind power (solar power) (Bloomberg, 2016). As Germany has set very ambitious targets in order to cut CO_2 emissions drastically, there is still much change ahead. Accordingly, the German electricity market has already changed dramatically and this change will continue. All of this makes the German power sector a very fertile ground for market research questions largely unaddressed so far. Lessons learned from the German case should therefore provide others with vital knowledge about how to manage renewable energy risk in modern liberalized electricity markets.

In the context of this work, we define production risk as the variations in the monthly revenues of a portfolio of physical (renewable) assets. Our results point to considerable heterogeneity of hedging efficiencies across technologies, locations, and seasons. Electricity futures – undoubtedly the most liquid exchange-traded derivatives in the German market – offer modest possibilities to transfer risk at best. For wind, there is some potential for risk reduction during winter months. In contrast, electricity futures are unsuitable to mitigate production risks for solar farms. We also test the hedging efficiency of more exotic derivatives – wind power futures – for the case of wind parks. These relatively new derivatives started trading in October 2016 at the EEX. Here, sizable risk reductions are possible (over 90%) which, however, strongly vary from location to location. Our analysis further reveals that alterations to the existing renewable generation portfolio can have a sizable impact on hedging efficiencies. In particular, our investigation of possible future scenarios in 2025 allows us to conclude that the potential for risk transfer through derivative products is likely going to rise significantly for wind power, whereas hedging solar risk will remain difficult. Even realistic amounts of 1-year changes can result in sizable changes of hedging efficiencies. Consequently, producers should constantly keep track of developments in the generation portfolio to adequately assess the potential for risk transfer through financial derivatives. Another major finding is our comparison of the old fixed price subsidy mechanism and its altered spot price related version. Interestingly, the new mechanism does not result in noticeable increases of the producer's revenue uncertainty.

Our study is closely linked with the large field of managing weather-related production uncertainty and basis risk in commodity markets. It is well known that these risks are of major concern for most commercial hedgers in commodity markets (Haushalter, 2000) and an active risk management of these quantities by means of financial derivatives actually results in an increase of firm value (Perez-Gonzalez and Yun, 2013). There is a significant amount of studies dealing with hedging of weather-related production risks. For example, Woodard and Garcia (2008) and Zhu et al. (2015) analyze the potential for risk reduction through the use of weather derivatives for the US and Canadian agriculture markets. They find large potential for the variance reduction of local production risks (up to 90%). In contrast to the purely temperature-driven exposures in the above studies, the hedging problem we face is far more intricate. Not only do we have to consider multiple dimensions of weather-related risks from wind speed, solar irradiation to aggregate temperature-driven electricity demand, but also how all of these variables contribute to the formation of wholesale electricity spot prices. Existing findings can consequently not easily be projected to our case and call for an in-depth analysis to foster the understanding of the management of local production risks for wind and solar assets. An assessment of the potential of risk transfer due to financial derivatives is furthermore important as the availability of insurance contracts has been shown to influence production and investment activities of economic agents. Cole et al. (2016) find that an introduction of weather-related insurance contracts has a significant impact on production decisions as such that market participants are willing to take more risks and adopt new high-yield production technologies. Cornaggia (2013) shows that there is a positive correlation between the supply of risk management instruments available to agricultural producers and aggregate productivity. An adoption of renewable electricity generation technology might therefore also be related to the availability of effective liquid hedging contracts. Our analysis offers insights into the efficiency of the derivative market in this regard.

The structure of our study is as follows. Section 2 details production risks and revenue computation for renewable generators in the German electricity market. Section 3 introduces our model framework, Sections 4 and 5 include our empirical analysis of un-

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[1] In an even more recent amendment ("EEG2016") the scheme was altered once again introducing competitive auctions for receiving subsidies. However, the link to wholesale market prices remains mostly unchanged.

[2] We ignore hydropower in this regard. It is true that some Scandinavian countries satisfy a large proportion of energy demand by hydropower. However, in most countries it is very difficult to implement this technology on a large-scale basis. Furthermore, pumped hydropower storage does not possess the intermittent characteristics of wind and solar power technology making their management much less problematic.

hedged and hedged renewable energy portfolios. Section 6 concludes.

2. Production risk of renewable generation

Our analysis is concerned with production risks of renewable generation which we define as variations in the monthly revenues of a portfolio of physical (renewable) assets. The renewable generating capacities of various technologies $u \in U$ can be situated at different locations $k \in K$ covering the German market area. To start with, let us consider a fixed price subsidy mechanism entitling producers of renewable energy to a fixed levy per unit of generated electricity. Such a setting mimics the original government-set feed-in tariff in Germany which holds for generation capacities installed until 2012.[3] Within this subsidy mechanism, the guaranteed fixed price F^u (in EUR per MWh) depends on the type of technology $u \in U$ only and is being paid for a duration of 20 years. We consider a more market-oriented compensation scheme in Section 5.2. As subsidies are being calculated and paid ex-post on a monthly basis, we choose monthly intervals for our analysis. The monthly revenue $v_T^{u,k}$ for a renewable generator using technology u at location k under the above market mechanism is consequently given by:

$$v_T^{u,k} = \sum_{t \in T} r_t^{u,k} F^u, \tag{1}$$

where $r_t^{u,k}$ corresponds to the amount of generated electricity (in MWh) from the physical asset in hour t and T is the set of all hours during the respective month. For simplicity, we assume that the producer is only concerned with the variance of his monthly revenues $\mathbb{V}ar[v_T^{u,k}]$.[4]

To hedge his risk the producer can decide to make use of exchange-traded financial derivatives by setting up a respective position at t_0. This derivative hedging strategy leads to a monthly payoff $h_{t_0,T}$ resulting in a hedging error $\varepsilon_{t_0,T}$:

$$\varepsilon_{t_0,T}(\theta) = v_T^{u,k} + \theta h_{t_0,T},$$

where θ corresponds to the position in the derivative instrument he chooses to minimize the variance of his (hedged) monthly revenue:

$$\arg\min_{\theta} \mathbb{V}ar_{t_0}[\varepsilon_{t_0,T}(\theta)].$$

In order to analyze the effectiveness of different derivative contracts the producer not only requires an understanding of the stochastic production of his local generation $r_t^{u,k}$ but also of the dependencies between drivers of his revenue stream and drivers of the respective derivative payoff $h_{t_0,T}$. Depending on the chosen financial derivative instrument, such drivers range from wholesale electricity prices to market-wide renewable generation. Consequently, the producer has to consider the sensitivity of his revenues to changes in wholesale electricity prices or needs to have information regarding how his (local) generation is tied to the overall production in order to set up the hedge positions.

3. Model framework: a residual demand model with local information

As shown in the last section, our analysis of hedging production risks necessitates a modeling framework that establishes a link between wholesale market prices and local renewable generation. The literature on electricity price modeling is vast. However, only a small subcategory of models actually serves our purposes.

Modeling approaches for electricity prices can broadly be separated into two categories. On the one side of the spectrum are approaches which heavily borrow from reduced-form models from equity- or interest rate markets. Early studies use low-dimensional stochastic processes to capture patterns such as mean-reversion and seasonalities (Lucia and Schwartz, 2002). In order to capture pronounced price spikes, unmatched in other commodity markets, Deng (2000), Cartea and Figueroa (2005), Geman and Roncoroni (2006), Seifert and Uhrig-Homburg (2007) or Hambly et al. (2009) consider variations of jump processes. Although these models generally share nice properties such as closed-form pricing formulas for derivatives, they are often difficult to use in the rapidly changing electricity markets. For instance, if, for some reason, there have been considerable changes in installed wind capacity one would usually expect volatility to be affected somehow. However, since power exchanges' liquidity of option contracts is very thin there is generally no reliable forward-looking information with regard to higher-moment price risk to look at in order to re-calibrate a reduced form model.[5] In extreme cases, all the available historical data can then be rendered useless.

The other extreme consists of so-called structural production cost models. Under these modeling approaches wholesale market clearing prices result from a cost minimization problem in which demand must be satisfied under certain side restrictions such as transmission constraints (Eydeland and Wolyniec, 2003). The approach requires very detailed information on technical peculiarities of power plants or environmental constraints of the whole power market in question. A significant drawback is the fact that such models generally only make predictions on expected price levels and do not allow inference on higher moment price risks. This disqualifies them as a viable tool for risk management purposes such as hedging. Still, the approach reveals how certain fundamental factors drive market prices and has therefore partly served as inspiration for the development of the last class of price models.

Hybrid structural models lie somewhere in between the two above categories - basically resulting in a trade-off between analytical tractability and the degree of granularity with which specific market characteristics are captured. As opposed to reduced-form approaches that try to grasp how prices move, this model class looks beyond prices and asks why do prices move in the first place (Eydeland and Wolyniec, 2003). Key fundamental factors driving prices consist of market-wide demand or supply-side variables related to the cost or availability of generation capacities. For instance, a more volatile demand process usually results in larger swings in wholesale spot prices. Existing hybrid modeling approaches range from slightly altered reduced-form models (e.g. Eydeland and Wolyniec, 2003 or Cartea et al., 2009) to more involved modeling frameworks varying in the number of fundamental factors considered and the kind of information being used for calibration (e.g. Burger et al., 2004; Coulon and Howison, 2009; Aid et al., 2013; Füss et al., 2015, or Ziel and Steinert, 2016). In electricity markets dominated by renewable generation, such as Norway or Germany, weather variables can play a major role for the characteristics of available power generation over time. Similar to other fundamental factors, their stochasticity can then be captured by well-established reduced-form modeling approaches. For example, autoregressive models have been shown to work well for the (univariate) modeling of wind speed and power (e.g.,

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[3] The subsidy mechanism is quite complex and possesses quite a few exceptions, primarily for small installations. We regard those to be of minor relevance for our analysis and omit these exceptions.

[4] We will justify the choice for this rather simple objective function in Section 4.3.

[5] Although future contracts tend to be very liquid in European power markets, they usually carry not much information with regard to volatility risk.

Brown et al., 1984; Mora-Lopez and Sidrach-De-Cardona, 1998; Caporin and Pres, 2012; Alexandridis and Zapranis, 2013) while Morales et al. (2009) and Papavasiliou and Oren (2011) both make use of vector autoregressive (VAR) models to capture the joint distribution of wind speed dynamics at various locations in the United States whereas Grothe and Schneiders (2011) combine autoregressive models with pair-copula constructions (PCC) in a similar setting for German wind speed data.

Nevertheless, studies considering renewable generation for power price modeling are still relatively scarce. Keles et al. (2013) and Cludius et al. (2014) propose methodologies to incorporate wind power and solar generation in reduced-form models whereas Wagner (2014) uses a simple residual demand framework that introduces new sources of risk by including solar and wind generation as additional fundamental factors. However, the above approaches all neglect the spatial distribution of the renewable generation portfolio completely. In order to address this, Hain et al. (2017) propose an extended modeling approach capable of capturing the local amount of installed renewable generation capacities at different locations. Using their framework allows us to make an assessment of local production risks and deduce hedging strategies based on financial derivatives.

We briefly discuss the main intuition behind Hain et al.'s electricity price framework for renewable-dominant markets and refer the interested reader to Hain et al. (2017) for a more detailed description. The approach basically consists of two model components. The first one corresponds to a residual demand model capturing the interaction between market-wide demand, market-wide renewable generation, and wholesale spot prices, similar to Burger et al. (2004) and Wagner (2014). The second component comprises the modeling of the joint distribution of weather variables and their mapping to local renewable electricity generation. The sum of all local variables then enters the first component in terms of the market-wide renewable power production.

We start with the first component. The basic idea is that conventional generators satisfy the corresponding (inelastic) demand in hour t adjusted for the uncertain amount of renewable generation $\bar{r}_t$ in the system.[6] To illustrate the idea, Fig. 1 shows the relationship between spot prices during peak- and baseload hours with both demand d_t as well as residual demand $\delta_t = d_t - \bar{r}_t$. As expected, the figures show that given a level of raw demand d_t there is still considerable variation in wholesale spot prices s_t. These variations (along the y-axis) are clearly reduced if we instead consider residual demand δ_t. Also note that for offpeak hours there are many cases of very low and even negative spot prices whereas demand was not even exceptionally low. A direct comparison with the residual demand - spot price relationship shows that these low prices were in fact caused by exceptionally large production levels from renewables. This shows that in a market with a significant presence of renewables such as Germany a modeling approach for wholesale electricity prices should account for the stochasticity from renewables. This leads us to the formal definition of the first component of the modeling framework.

Model Component 3.1. The model for hourly wholesale day ahead spot prices s_t is

$$s_t = f_t(\delta_t) + \sigma_t \tag{2}$$

$$\delta_t = d_t - \bar{r}_t \tag{3}$$

where

Fig. 1. Empirical relationship between load, residual load, and spot prices The figure depicts the relationship between load and spot price (top two figures) as well as between residual load and spot price for peak- and offpeak hours. Data ranges from January 2010 to mid 2014 (EEX-transparency platform). Peakload hours correspond to all hours within 8 am to 8 pm (offpeak to remaining ones).

$f_t(.)$ corresponds to the supply curve function, and σ_t is a residual volatility process.

The supply function $f_t(.)$ thus maps the current inelastic demand[7] to a respective hourly day-ahead spot price s_t. This curve basically results from an auction which orders the generators according to their bids. Generators offer their generating capacities at marginal costs and market-wide inelastic residual demand δ_t determines the intersection with the supply curve and with it the resulting market clearing price. σ_t is an error term accounting for randomness unexplained by the structural modeling framework such as capacity outages and various power grid constraints.

While one could model δ_t directly, the approach recognizes that doing so would have several drawbacks. Most importantly, it would mix sources of risk from the demand- and supply-side and aggregate generation of renewables from different sources that are expected to behave very differently. In particular, output from renewable sources is much more dependent on current weather conditions than conventional generation. On top of that, generation from renewable sources at different locations is potentially very different due to current local weather conditions and differences in (local) installed capacity. Therefore, we choose not to model the aggregate generation of a specific renewable technology directly but rather focus on its local constituents. This results in the following description of the second main model component:

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[6] Because the feed-in of wind and solar is basically free of marginal cost, Hain et al. (2017) assume their generation bids to be accepted on the wholesale market independent from wholesale market prices (which is true, unless very negative prices occur).
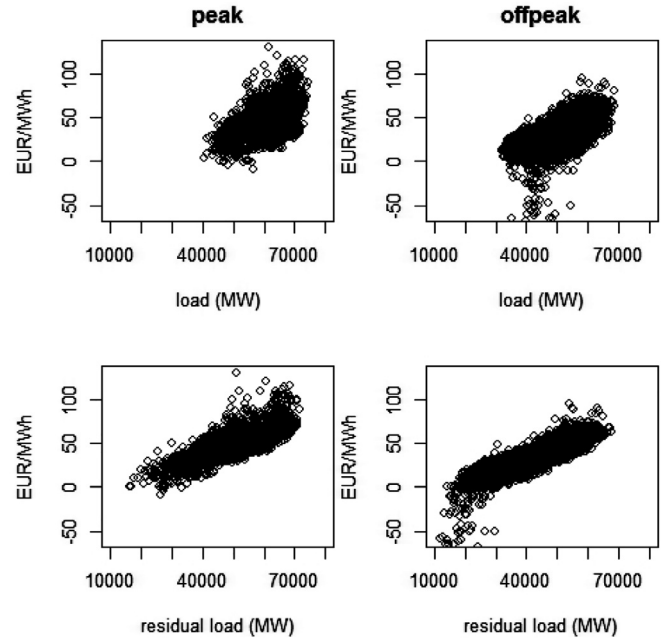
[7] The assumption of inelastic demand is a restrictive but widely adopted assumption throughout the literature. While the large part of demand can really be assumed to be price-inelastic (the vast majority of demand participates at the maximum offer-price every day in the day-ahead market auction), there exists a small share that would A) be willing and B) is technically able to reduce or even forfeit its demand at very high price levels and at short notice. Because this would only take effect at very high prices, i.e. when renewable generation is at very low levels, we do not expect this to have noticeable effect on our analysis and thus ignore elastic demand for our study.

Model Component 3.2. The model for the hourly renewable generation process $\bar{r}_t$ is

$$\bar{r}_t = \sum_{u \in U} \bar{r}_t^u \qquad (4)$$

$$\bar{r}_t^u = \sum_{k \in K} g^{u,k}(y_t^{u,k}) \qquad (5)$$

where

K is the set of different locations covering the market area,
U corresponds to the set of different renewable technologies in the market,
$\bar{r}_t^u$ is the technology specific aggregated generation,
$g^{u,k}(.)$ is the production curve mapping weather conditions to output (in MWh), and
$y_t^{u,k}$ is the location- (k) and technology-specific (u) weather variable.

The approach thus incorporates the modeling of the distribution of local weather conditions and their corresponding mapping $g^{u,k}(.)$ to local and with it to market-wide generation of a certain renewable technology.[8] In other words, one recursively adopts the basic idea behind hybrid structural modeling approaches by looking at the drivers (weather) of renewable generation[9] which itself drives wholesale market prices.

4. Empirical analysis

With the electricity price modeling framework for renewable-dominant markets at hand, we are now ready to analyze production risks and the potential for risk transfer through financial derivatives for wind and solar parks at different locations in Germany by means of a comprehensive simulation experiment. We first calibrate our model to recent data to obtain a realistic representation of variables of interest and then analyze the risk of unhedged and hedged positions for the case of the fixed price subsidy mechanism.

4.1. Model calibration and simulation setup

We follow the approach in Hain et al. (2017) to calibrate the model and proceed as follows. For Model Component 3.1 we make use of data published at the EEX-Transparency platform from late 2009 to mid 2014 consisting of market-wide demand, market-wide renewable generation as well as wholesale day-ahead spot prices. We use demand, renewable generation, and wholesale prices to estimate both the supply function $f_t(.)$ as well as the process for the residual volatility component σ_t. Based on the data we can infer the time series of residual demand $\delta_t = d_t - \bar{r}_t$ which is used to estimate f_t. We choose a parametric function, similar as
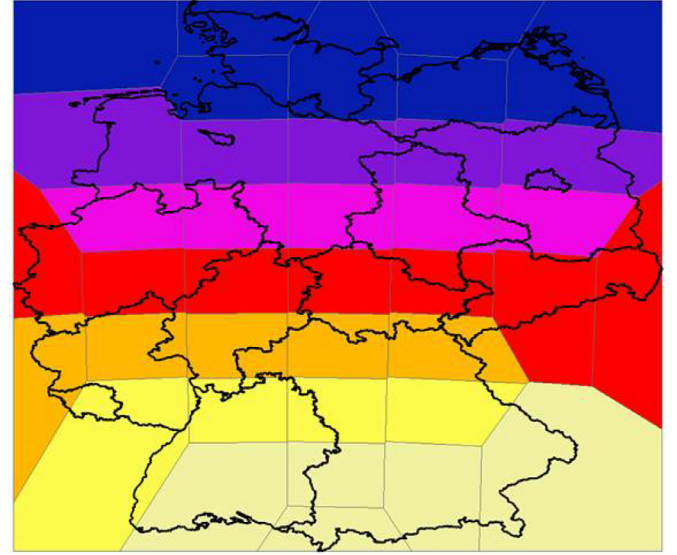

Fig. 2. Weather cells of German market area The figure shows the grid of weather cells that covers the German market area. Colors indicate y coordinates to ease interpretation for figures in other subsections.

in Burger et al. (2004) or Wagner (2014), whose parameters can vary for peak- and offpeak hours.[10] Parameters are then estimated by minimizing the squared differences between wholesale spot prices s_t and model values $f_t(\delta_t)$. Using the estimated supply function $f_t(.)$ and spot prices s_t results in the time series of residuals $\sigma_t = s_t - f_t(\delta_t)$ representing all variation unexplained by the residual demand modeling framework. This process is then in turn modeled by a seasonal ARIMA process with GARCH innovations. To complete the calibration of this model component we also need to pin down the dynamics of market-wide demand. This is achieved by fitting a seasonal ARIMA process to the hourly time series of d_t.

A key ingredient for the calibration of our second model component lies in the information regarding the spatial distribution of renewable generators. Since there are more than 1.5 million renewable energy plants in Germany (Bundesnetzagentur, 2015), we simplify this diversity and aggregate the installed capacity. We choose to represent the spatial distribution of renewable capacity by $K = 38$ locations corresponding to 38 weather cells (see Fig. 2).[11] We then allocate the capacity of wind and solar generators according to EnergyMap (2016). The spatial granularity is primarily chosen to limit the computational burden in the estimation and scenario generation of our weather model later on. We make use of a historical time series of solar irradiation and wind speeds at 120m above ground supplied by Anemos (2016) for each of the $K = 38$ locations in Germany.[12] This data is in turn used to estimate the model for the dynamics of the local weather variables $y_t^{u,k}$. We account for location- and technology-specific seasonal patterns and non-normal behavior and furthermore impose

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[8] Given the current structure of the German electricity market, both wind and solar are by far the most important technologies which is why Hain et al. (2017) restrict their modeling to these two candidates, that is $u \in (w, s)$.

[9] Apart from wind and solar, only generation based on biomass and hydro contributes significantly (https://www.bdew.de/media/documents/20170710_Foliensatz-Erneuerbare-Energien-EEG_2017.pdf). However, we do not account for them for the following reasons: Hydro power plants are highly flexible for the vast majority of capacity and are traded to generate at times of high prices. Thus, their generation profile is not stochastic but highly dependent on expected electricity prices and should not be deducted when calculating residual demand. The electricity generation of biomass plants on the other hand is quite independent from electricity prices and rather constant. The Germany-wide biomass portfolio achieved more than 6000 full load hours during the years 2011–2015 on average. Therefore, we believe that it makes only a small difference to our analysis whether to consider biomass for the residual load or not. For the sake of simplicity we chose to ignore biomass when calculating the residual load.

[10] Note that this model specification refrains from modeling an explicit dependence on fuel prices. Appendix Appendix A gives some more details with regard to the parametric form of f_t.

[11] Note that the German and Austrian power grid actually belong to one market area. However, for simplicity, we restrict our analysis to the German market area only and ignore any renewable generation capacities located in Austria.

[12] In detail, the data is generated through downscaling of reanalysis data from the NASA program Modern-Era Retrospective Analysis for Research and Applications (MERRA) applying the mesoscale model MM5 (PSU/NCAR, 2016). It has a temporal resolution of 10 minutes (spanning from 1990 to 2012) and a spatial resolution of 20km x 20km. We then compute location-specific averages both in the time as well as in the spatial dimension which results in representative hourly values for each of our $K = 38$ weather cells.

a VAR structure for the joint distribution of wind speed and solar irradiation.[13] To estimate the location-specific (parametric) mapping functions $g(.)^{u,k}$ we then use 3 data sources from late 2009 to mid 2014: (1) the above mentioned time series of market-wide renewable generation (technology-specific), (2) a panel data set of weather variables from the MERRA database used for the calibration of the weather dynamics, and (3) the amount of (local) renewable capacity over time from EnergyMap (2016). In simple terms, local weather variables are suitably weighted and constrained to match the aggregated renewable generation to arrive at an estimate for all location-specific mappings.[14] For $g(.)^{u,k}$ we choose a 3-parameter logistic-function (wind power) and a second-order polynomial (solar power) and estimate parameters by minimizing the sum of squared residuals.[15] Also note that we make use of realized weather data to calibrate our weather model which we then actually use as a proxy for day-ahead forecasts in our simulations.[16] A first analysis of the weather variables shows that the underlying weather variables driving the revenue distribution are governed by a systematic component: For the case of wind speed over 50% of locations share a correlation coefficient of over 65% with each other, whereas for solar, this goes as high as 90%. Note however, that the very high number for the latter is mostly caused by pronounced seasonal and day-and night trends. Nevertheless, dependencies tend to drop by distance: For a weather cell in the north and south correlation of wind speed can get as low as 25%. Appendix A.3 offers some additional insights into the model's capability of explaining the empirical distribution of our data set.

We make use of simulations to deduce corresponding risk measures and hedge-ratios and set the number of scenarios to $N = 1000$. One trajectory of wholesale power prices necessitates the simulation of all state variables: (1) weather variables; (2) market-wide demand; (3) residual volatility. If not stated otherwise, we analyze each month separately and create the revenue distributions of renewable portfolios by conditioning the state variables to equal their mean values of the preceding month.

4.2. Assessment of production risks

In what follows, we analyze the risks an owner of a 1-MW equivalent of renewable generation capacity (wind or solar) faces if his physical assets are located at one of the $K = 38$ weather cells. For simplicity, we use the configuration of 2013 as given. Fig. 3 shows the distribution of both wind and solar power for this scenario. The capacity installed at a given location is held constant over the year, as otherwise a direct comparison of risks and hedging efficiencies could be biased. Note that we do not alter the overall generation portfolio but just assume that a certain fraction at each location (1 MW) belongs to the wind park or solar farm of the representative producer. We set the guaranteed fixed price F^w

(F^s) to 80 (100) EUR/MWh for wind (solar) which corresponds to average values for the feed-in-tariff of rather new renewable producers published in AEE (2014).

Before assessing the potential for risk transfer through the use of financial instruments it is instructive to have a closer look at how risky unhedged renewable portfolios actually are. In particular, it is of interest to see major differences among technologies, seasons, or locations. We therefore simulate the revenue distribution for representative producers at all 38 locations both for wind and for solar.

In order to develop some intuition for the general revenue uncertainty and tail risks we discuss the characteristics of volatility and 1% quantiles ("Value-at-Risk"). To ease interpretation and to set the risk into perspective, we normalize the aforementioned risk measures by the expected output of both technologies for all locations and every month. Compared to looking at absolute values, normalized figures facilitate comparisons across technologies.

Fig. 4 shows the simulated revenue distribution of wind and solar generation of an exemplary location in July. Although considerable uncertainty is present for both production technologies, volatility is much more dominant for the case of wind power. Also note the slight differences in symmetry of the distributions with solar exhibiting a longer left tail (negative skewness). As shown in Fig. 5, average monthly revenue volatility across seasons and locations is sizable and amounts to 17% (6.5%) for wind (solar). The risk measures furthermore reveal striking differences. For example, volatility levels range somewhere between 15 and 25% during summer months for the case of wind power whereas for solar corresponding values are as low as five percent. This is accompanied by more extreme downside risk. For instance, in the case of wind power there are some locations for which we see production levels dropping to just about 50% of expected values during specific months of the year. This stands in strong contrast to solar generation where the lowest one percent quantile is around 70% in December or January but stays well above 80–85% for most of the year.[17] We also observe pronounced seasonal patterns for both production technologies. For solar, there is a clear pattern of larger deviations during winter seasons whereas the situation for wind looks much more varied. There are both seasonal patterns (larger volatility during summer for some locations) as well as cross-sectional ones (larger average volatility in northern locations).

In summary, the analysis of unhedged renewable energy portfolios reveals large uncertainties associated with future cash flows. To set these risks into perspective with other asset classes we approximate the associated uncertainties with volatility indices published by the CBOE (2017) which are basically model-free measures of the forward-looking 30-day volatility derived from a portfolio of liquid out-of-the-money option contracts. In detail, we consider the respective indices for the 10-year US treasury rate (fixed-income), the EUR/US-exchange rate (foreign-exchange), the S&P500 index (equities), as well as for crude oil prices (commodities) from early 2007 to early 2017. A comparison of (annualized) volatilities of monthly revenues of wind parks ($\approx59\%$) or solar farms ($\approx23\%$) with other asset classes such as fixed-income (7%), foreign-exchange (11%), equities (20%), or other energy commodities[18] (38%) then shows that investors face large exposure towards weather-induced uncertainty, especially for the case of wind. Con-

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[13] This approach loosely follows Morales et al. (2009) and Papavasiliou and Oren (2011). More details can be found in Hain et al. (2017)

[14] Note that we actually observe renewable production for wind and solar power separately for four different so-called "balancing areas". Taken together these 4 areas form the complete German market area. Each weather cell in turn belongs to one of these balancing areas. We estimate one representative mapping function $g(.)$ for all weather cells within a corresponding balancing area by weighting each cells' weather variables according to its location-specific capacity. This ensures that cells containing a disproportional large amount of capacity are also assigned a larger weight in the estimation process.

[15] The choice of parametric functions is motivated by typical production patterns of these two types of generation technology.

[16] Since we lack a large panel data set for day-ahead forecasts of local weather variables we use realized actual values of the weather variables both for the calibration of the weather model as well as for the mapping functions. This introduces a slight inconsistency as we try to model the behavior of day-ahead expectations. However, since we do not expect any systematic bias from such an approach the impact should be minor.

[17] Note that solar generation levels are very low during winter (often times well below 10% of summer values) which means that the absolute amount of revenue uncertainty during the more volatile seasons is much lower.

[18] Note that although commodities are very different from each other, crude oil is among the most volatile ones and thus works well as an approximate upper bound for our comparison.
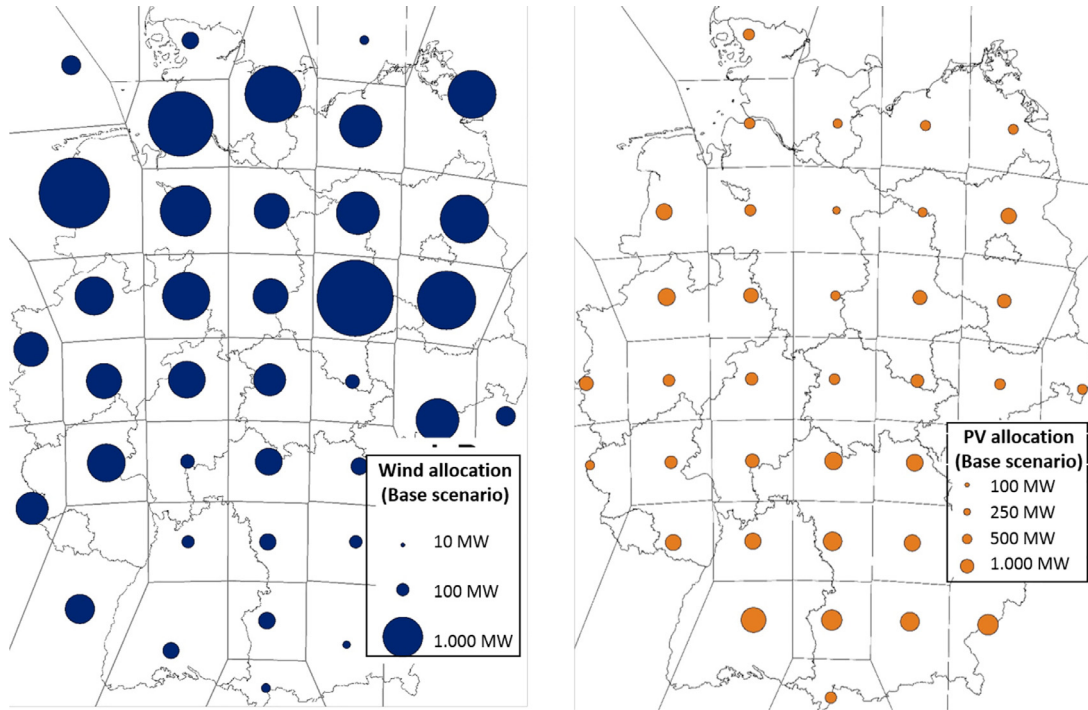
Fig. 3. Spatial distribution of renewable capacity. The figure shows the spatial distribution of renewable capacity for wind (left) and solar (right) for the base scenario.
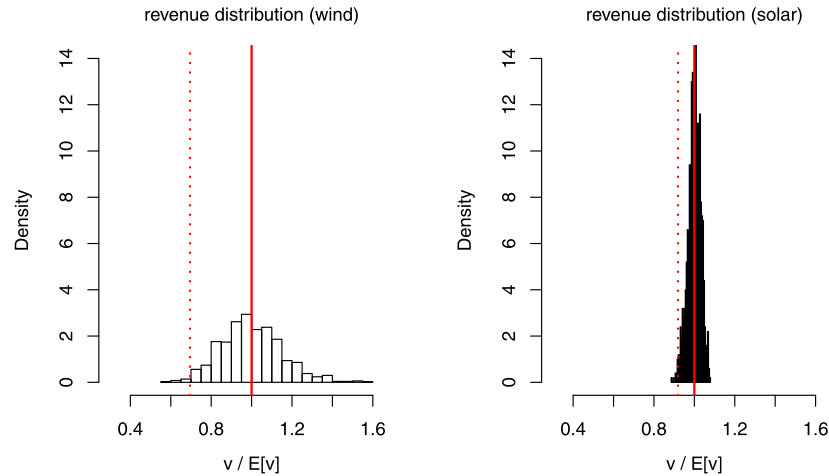

Fig. 4. Unhedged revenue distributions. The figure shows examples of simulated revenue distributions for wind (left figure) as well as for solar (right figure) in July for an exemplary location in the northwest of Germany. The solid line corresponds to the mean whereas the dotted line is the 1% quantile.

sequently, it is all the more important to have effective hedging instruments in place.

4.3. Hedging by means of financial derivatives

We investigate the hedging effectiveness of different derivative instruments by looking at the magnitude of variance reduction on a monthly basis. The metric to compare the efficiency of different hedging positions is given by the resulting variance reduction compared to the unhedged case ($\theta = 0$):

$$\Delta \mathbb{V}ar_{t_0} = 1 - \frac{\mathbb{V}ar_{t_0}[\varepsilon_{t_0,T}(\theta)]}{\mathbb{V}ar_{t_0}[\varepsilon_{t_0,T}(0)]} \tag{6}$$

Minimizing cashflow variance is a widely established approach to reduce an investor's price exposure (e.g. see Figlewski, 1984; Ederington and Salas, 2008, or Branger et al., 2011). We therefore regard this choice as a reasonable natural starting point for the as-

sessment of hedging performance within the German power market.[19] Note that our measure of hedging effectiveness is a conditional one, indicated by the time-index t_0. We set the hedge up one month in advance (at t_0) and condition all state variables (e.g. weather variables $y_t^{u,k}$ or demand d_t) to equal their respective mean value.[20] We furthermore bypass any in-sample bias by using a different set of simulation scenarios to deduce the optimal position in the hedging instrument θ ("hedge-ratio") and to evaluate the hedging efficiency according to Eq. (6).

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[19] It is still undecided if electricity futures do carry significant risk premia (e.g. see Bieger-König, 2013) and the lack of data regarding wind power futures prevents us from quantifying the "'market price wind risk" in a meaningful manner. Consequently, we regard it more sensible to ignore hedging costs in terms of risk premia in the following analysis.

[20] Note that we ignore interest rates due to their low volatility (relative to production and price risks of power markets) and the short hedging horizon.
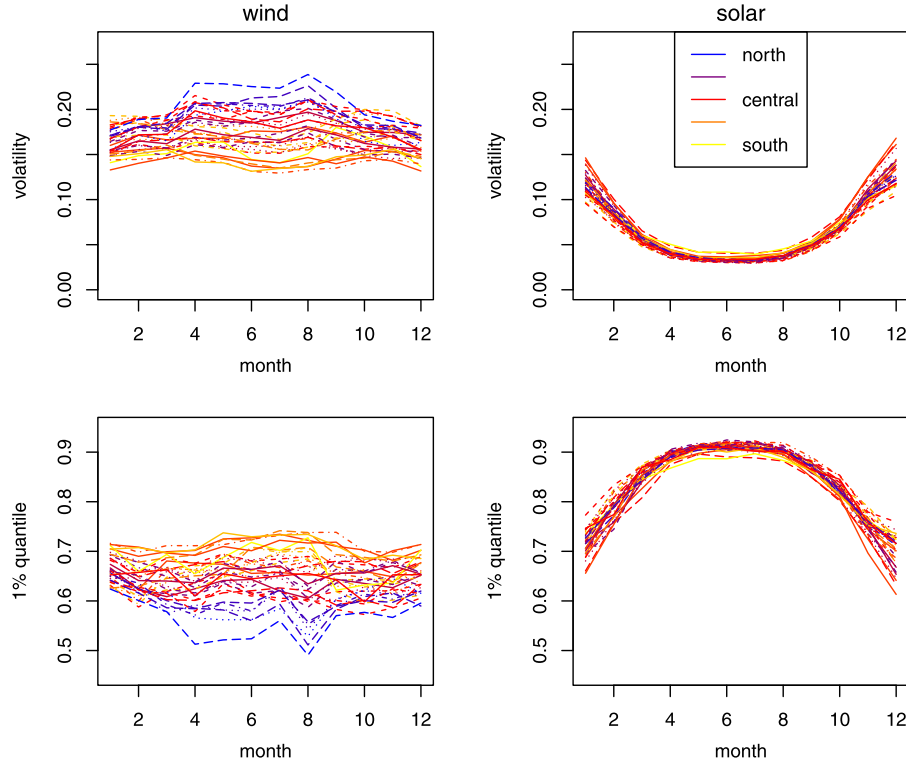
Fig. 5. Risks of unhedged revenues. This figure exhibits the volatility (top two figures) as well as the 1% quantile (bottom two figures) of the (monthly) revenue distributions (both scaled by the expected production level) for wind (figures on left hand side) as well as for solar (figures on right hand side) for all $K = 38$ locations and months separately.

Our hedging problem is related to the study of Brown and Toft (2002) in which optimal hedges for a firm facing multiplicative hedgable (price) and unhedgable (quantity) risks are discussed. The authors deduce an optimal hedge portfolio using both linear (futures) and non-linear (options) contracts. In particular, they point out the importance of non-linear contracts in the presence of high levels of correlation between price and quantity risk. Within our setting, the firm (producer) faces unhedgable (quantity) risk only and can choose between two derivative contracts: (1) a price-related future contract and (2) a quantity-related contract (for the case of wind power only). Both instruments are imperfect hedges as pointed out within the next two subsections and our hedging exercise reveals how useful the derivatives markets are in mitigating location-specific production risks for different technologies and seasons.

4.3.1. Electricity futures

Electricity futures are traded quite actively at the European Energy Exchange (EEX) (see Wagner, 2014). They offer conventional producers as well as consumers of electricity a possibility to hedge against adverse price developments in the future. For instance, an owner of a coal-fired power plant might want to secure the margin of his business by selling his production forward for a fixed price per unit of electricity delivered, thereby mitigating the risks of larger price drops during the nearer future. Renewable generation has been shown to possess a significant impact on the wholesale market price which is the underlying index for most electricity futures offered by the EEX. Facing non-traded (local) quantity risk, the renewable producer now needs to analyze how this uncertainty is associated with swings in wholesale spot prices in order to assess its potential as a valid hedging instrument.

We consider baseload futures contracts with a monthly delivery period. A long position in such a derivative entitles the buyer to receive one MWh of electricity for every hour of the contracted

delivery month.[21] The monthly payoff from the electricity future is consequently given by:

$$h_{t_0,T} = \sum_{t \in T} s_t - f_{t_0,T}^e$$

where $f_{t_0,T}^e$ is the time-t_0 price of the electricity future whose delivery period consists of all hours $t \in T$ (and coincides with the relevant time interval of the physical exposure that is to be hedged). The future price at t_0 is given as follows:

$$f_{t_0,T}^e = \mathbb{E}_{t_0}^{\mathbb{Q}}\left[\sum_{t \in T} s_t\right] \tag{7}$$

Note that the expectation in Eq. (7) is taken with respect to the risk neutral measure $\mathbb{Q}$, thus potentially containing risk premia for all kinds of non-traded risk factors. As our focus is set on the potential for risk reduction and not on the costs of hedging we ignore potential premia and set them to zero allowing us to compute Eq. (7) based on a calibration under the physical measure $\mathbb{P}$ (see Section 4.1). The optimal number of futures contracts θ can be interpreted as follows: for 1 MW of installed capacity of either wind- or solar power the producer enters θ futures contracts that each deliver 1 MW of power during the respective month.

Fig. 6 exhibits both the resulting hedging efficiency as well as the optimal hedge position. Clearly, the overall capability of electricity futures as valid instruments for mitigating production risk is rather limited. While for wind power variance reduction rises as high as about 16% in several instances, the potential for risk reduction in case of solar is virtually nonexistent. But also for wind power, the hedging efficiency drops severely in summer. This drop

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[21] Besides monthly, quarterly and yearly contracts there is also the possibility of purchasing power just for delivery during specific times of the day (e.g. peak hours). As a general rule, liquidity drops the further away the delivery period is.
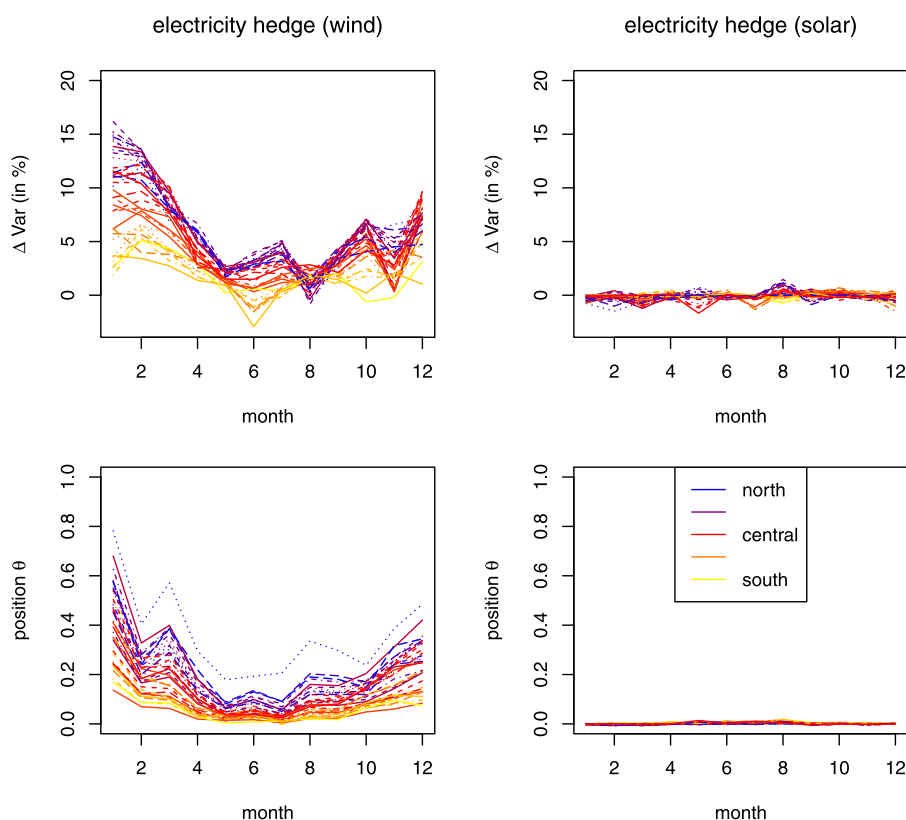
Fig. 6. Hedging efficiency of electricity futures. The top two figures visualize the hedging efficiency of electricity futures for wind (top left) as well as solar (top right) for $K = 38$ locations and each month separately while the bottom two figures show the optimal position θ in the electricity future for wind (bottom left) and solar (bottom right).

can mainly be attributed to the pronounced seasonality of solar generation. Solar power generation is extremely low in winter but in summer both solar and wind contribute significantly to aggregate renewable production and thus shape residual demand levels together. Consequently, production swings from both technologies interfere with each other. Once a decrease of one technology is accompanied by a simultaneous increase in the other this might leave the spot price unchanged and explains both why the hedging efficiency for the case of wind drops during summer season and remains extremely low for solar throughout the year.[22] We also find a slight advantage in terms of risk reduction for owners of wind parks located in northern locations which is most likely explained by the larger amount of installed wind power capacity in the north. We will elaborate on this in the following two subsections.

For the case of solar, we additionally test the possibility of using electricity futures written on spot prices during peak hours only. As there is no solar production during night time, price variations during this time interval should be unrelated to this source of weather risk, potentially distorting the hedging efficiency of the electricity future contract written on the hourly spot prices of all hours of the day. However, results for hedging efficiency are only slightly better with changes of at best 0.5%, offering hardly any improvement over the baseload contracts.

For wind power, the optimal hedge is usually a long position. Intuitively, this makes sense since large increases in electricity prices are often times associated with a lack of wind power in the

system. Consequently, states of high spot prices tend to be associated with drops in revenues of wind power producers justifying a long position in the futures contract. These positions tend to approach zero in most cases during summer seasons due to the above outlined elevated activity of both wind and solar generation. For solar, it is optimal not to enter the derivatives market at all. Overall, electricity futures are a rather poor hedge for technology-specific local production risks in Germany, especially compared to other commodity markets (e.g. agriculture) in which derivatives yield hedging efficiencies of up to 90% (e.g. see Zhu et al., 2015).[23]

4.3.2. Wind power futures

The increasing presence of renewable generation has caused several power exchanges to introduce products with a specific focus on weather-related risks. One example for such a new product are wind power futures at the EEX, which started trading in October 2016.[24] These weather-related derivatives are tied to the market-wide aggregated wind power production and thus allow wind producers to hedge against adverse (systematic) market-wide production reductions. Their general advantage over derivative instruments linked to electricity prices lies in the fact that their payoff is dictated by wind power generation only. Electricity futures on the other hand are driven by other risk factors such as temperature-driven demand or power production coming from so-

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[22] Such seasonal patterns in hedging efficiencies are rather uncommon but not restricted to our case. For example, Stulec (2017) shows that revenues from beverage sales in Croatia can be hedged by temperature derivatives to some degree but the feasibility of the strategy seems to be limited to the month of August only.

[23] Of course, in agriculture, producers usually face a multiplicative price-quantity risk which also explains to a certain extent why price-based derivative products work better in this case. Nevertheless, the analysis clearly shows the lack of potential hedging tools at hand in this market. We thank a referee for pointing this out.

[24] Another related new product is the so called cap future suited to hedge spike risk in the intraday market which began trading in late 2014.
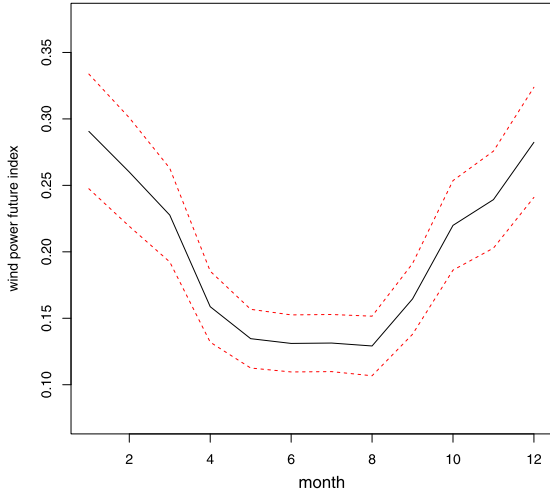
Fig. 7. Model values of wind power futures The figures highlights model values for the expected wind power future index ($f_{t_0,T}^w$) along with +/- 1 standard deviation bounds for all months of a year.

lar technology. As shown in the previous section, this limits their potential as hedging instruments considerably.

The underlying index, which wind power futures contracts are settled against, is the market-wide hourly wind generation normalized by the hourly available wind power capacity.[25] The wind power index future $f_{t_0,T}^w$ and the payoff $h_{t_0,T}$ from setting up the position at t_0 and holding the contract until maturity reads as follows:

$$f_{t_0,T}^w = \mathbb{E}_{t_0}^{\mathbb{Q}} \left[n^{-1} \sum_{t \in T} \frac{\sum_{k \in K} \bar{r}_t^{w,k}}{\sum_{k \in K} c_t^{w,k}} \right]$$

$$h_{t_0,T} = \left(n^{-1} \sum_{t \in T} \frac{\sum_{k \in K} \bar{r}_t^{w,k}}{\sum_{k \in K} c_t^{w,k}} - f_{t_0,T}^w \right) N \tag{8}$$

with n being the number of hours during the interval of delivery, N the notional amount of the future contract (e.g. 1 EUR), and $c_t^{w,k}$ the total amount of installed wind power capacity in region k at hour t. The index future value can consequently be regarded as the expected market wide average wind power capacity factor during a specific time interval with values ranging between zero (no wind production whatsoever) and one (all wind power assets producing at their maximum capacity).[26] Consequently, each individual producer is still exposed to some degree of basis risk and it is ex-ante unclear how effective the hedge is for physical assets located at different parts of the market area. Fig. 7 visualizes the model values for wind power futures for all months of a year. As expected, there is a pronounced seasonal pattern with larger production levels during autumn and winter season. Volatility (i.e. the one-month ahead uncertainty regarding the payoff from the contract) on the other hand does not vary considerably over the year.

Fig. 8 reveals that the hedging efficiency is significantly larger than in the case of electricity futures. On average the hedging efficiency is higher than 50% for three quarters of the locations and higher than 70% for more than half of the locations providing evidence for considerable potential for risk transfer through this new kind of derivative instrument. However, Fig. 8 also shows that there is a sizable amount of heterogeneity among the various lo-

cations. This might warrant a closer look at the properties of the wind power portfolio.

Clearly, hedging efficiencies tend to be considerably higher for locations lying in northern parts of Germany (note the color pattern in Fig. 8). This raises the question of how the amount of installed capacity is related to the effectiveness of this hedging strategy. Fig. 9 visualizes the relationship between the (local) wind power capacity versus average hedging efficiency of wind power futures over the year for all locations in question. Indeed, there is a general tendency of larger variance reduction levels for regions exhibiting a larger amount of installed capacity which tend to be mostly located in northern parts of Germany. Intuitively, this makes sense since locations with a large amount of installed capacity should have a disproportionally larger impact on market-wide generation than areas in which fewer wind turbines are located. As a result, the hedging efficiency of wind power futures for these regions tends to be higher as well. However, note that this relationship is likely to be affected by confounding factors such as the mean, volatility, or dependencies of wind speed of various locations. Nevertheless, the relationship depicted in Fig. 9 can serve as a quick back-of-the-envelope calculation to assess the potential for risk transfer through wind power futures.

Fig. 8 also shows that the producer optimally enters a short position in the derivative contract in order to hedge himself against drops in market-wide wind power production, a state which is usually associated with low local revenues as well. The optimal positioning θ in wind power futures exhibits interesting seasonal and cross-sectional patterns. For instance, while θs are considerably smaller than 1 (in absolute terms) for most southern locations they turn larger than 1 for more northern ones. Also, we observe considerable time-variation in short-positions, especially for offshore locations in the north where θ rises by as much as 100% during the summer season. These can probably best be explained by looking at the formal definition of the minimum variance hedge ratio θ:

$$\theta = -\frac{\mathbb{C}ov[v_t^{u,k}, h_{t_0,T}]}{\mathbb{V}ar[h_{t_0,T}]}$$

$$= -\frac{\rho_{v,h}\sqrt{\mathbb{V}ar[h_{t_0,T}]}\sqrt{\mathbb{V}ar[v_T^{u,k}]}}{\mathbb{V}ar[h_{t_0,T}]}$$

Larger dependencies to market-wide production and larger location specific volatility thus result in larger short positions. This explains why more northern locations necessitate more "leverage" in terms of higher θs compared to southern locations. The pronounced time-variation for some locations in the north seems to stem from the fact that wind power future volatility is not changing by too much over the year (see Fig. 7) whereas the location specific volatility does (see Fig. 5).

Overall, wind power futures can be regarded as very effective hedging instruments when compared to plain vanilla electricity futures, although the potential for risk reduction is strongly dependent on the location in question. Notably, the portfolio configuration of the renewable generation capacities seems to play a major role for the amount of risk that can be managed by means of financial derivatives. This motivates our assessment of the impact of changes in the renewable generation portfolio in the following section.

5. Alternative scenarios

Within this subsection we investigate several important deviations from our baseline scenario. First, we assess how changes in the renewable generation portfolio impact our hedging results (both on a short and long-term basis). Second, we analyze a more

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[25] The index is computed according to data and a meteorological model provided by DWD and EuroWind GmbH. For more information, refer to EEX (2015).

[26] Just as in the case of electricity futures we once again set risk premia to zero to compute $f_{t_0,T}^w$.
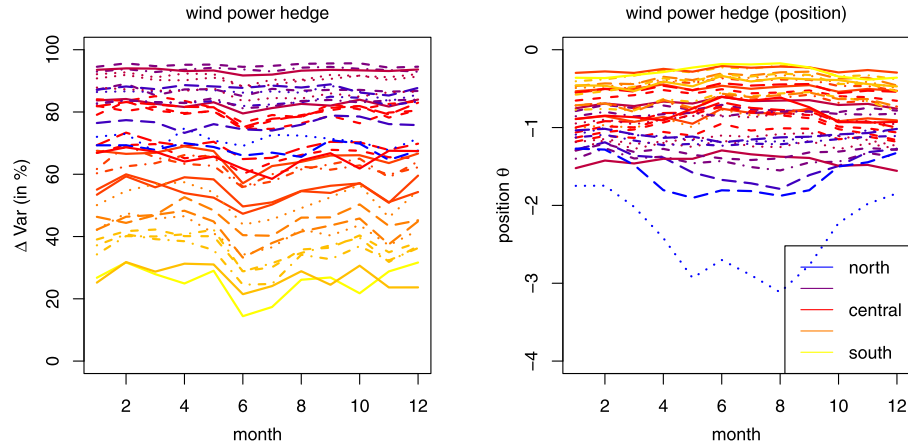
Fig. 8. Hedging efficiency of wind power futures. The left figure visualizes the hedging efficiency of wind power futures for all $K = 38$ locations in Germany while the right figure shows the corresponding optimal position θ in the wind power future contract.
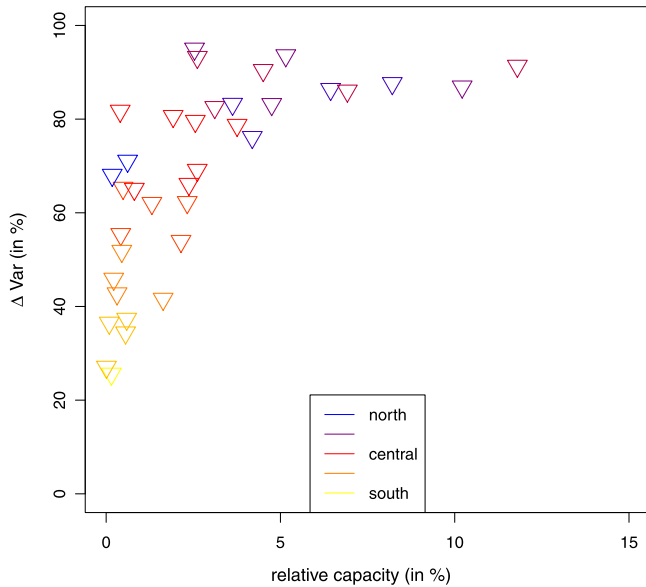

Fig. 9. Hedging efficiency of wind power futures vs. wind power capacity. The figures shows the dependency between installed (relative) wind power capacity and the (yearly) average hedging efficiency of wind power futures for all locations.

Fig. 10. Spatial distribution wind power capacity expansion The figure shows the (hypothetical) spatial distribution of wind power capacity additions for 2025.

market-oriented subsidy mechanism which introduces dependencies to wholesale market prices into the revenue (objective) function of the producer. And third, given the fact that the relevant temperature variables within our investigation are stationary, we look at other hedging horizons (e.g., yearly) as well.

5.1. Alterations to the renewable generation portfolio

The last section suggested that the amount of installed capacity in a region has a significant impact on the hedging efficiency of derivative products. On top of that, we know that the renewable generation portfolio is in constant change. For instance, there have been tremendous amounts of capacity additions for wind and solar in Germany from 2009 on (see EEX, 2016) and this trend is likely going to continue. New plans of fostering investment into renewables to satisfy 55% of electricity demand by renewable technologies by 2035 are already laid out in the altered version of the EEG in 2016. It is thus imperative to answer the question of how sensitive hedging efficiencies for different derivative instruments are to alterations in the renewable generation portfolio - a question
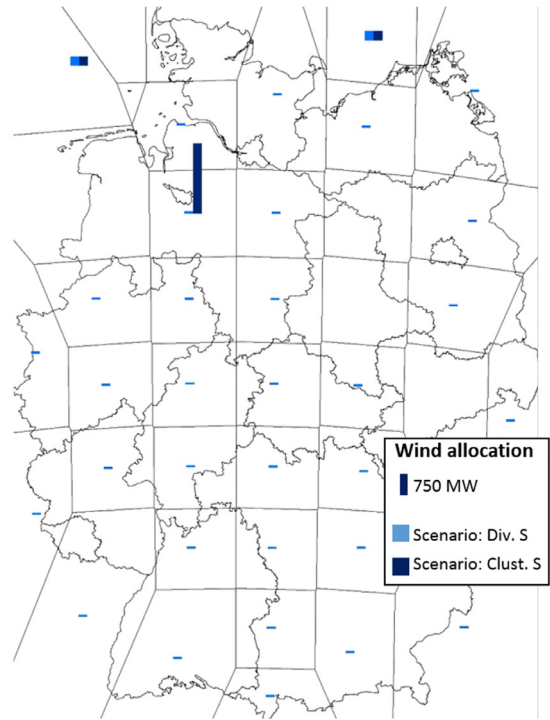
which has, to the best of our knowledge, not been addressed so far. We look at future changes in the renewable portfolio on a short-term horizon (1-year) as well as on a long-term horizon (10-year). This way, we provide information for both owners of existing physical assets as well as for potential investors assessing the financial consequences associated with the ownership of renewable generation technology.

To capture realistic amounts of a yearly change in the renewable generation portfolio we have to define (1) the total amount of (short-term, S) capacity additions for each technology and (2) how we distribute this new capacity among the $K = 38$ locations across the German market area. For (1) we take similar values as proposed in the EEG 2016[27], whereas for (2) we consider two hy-
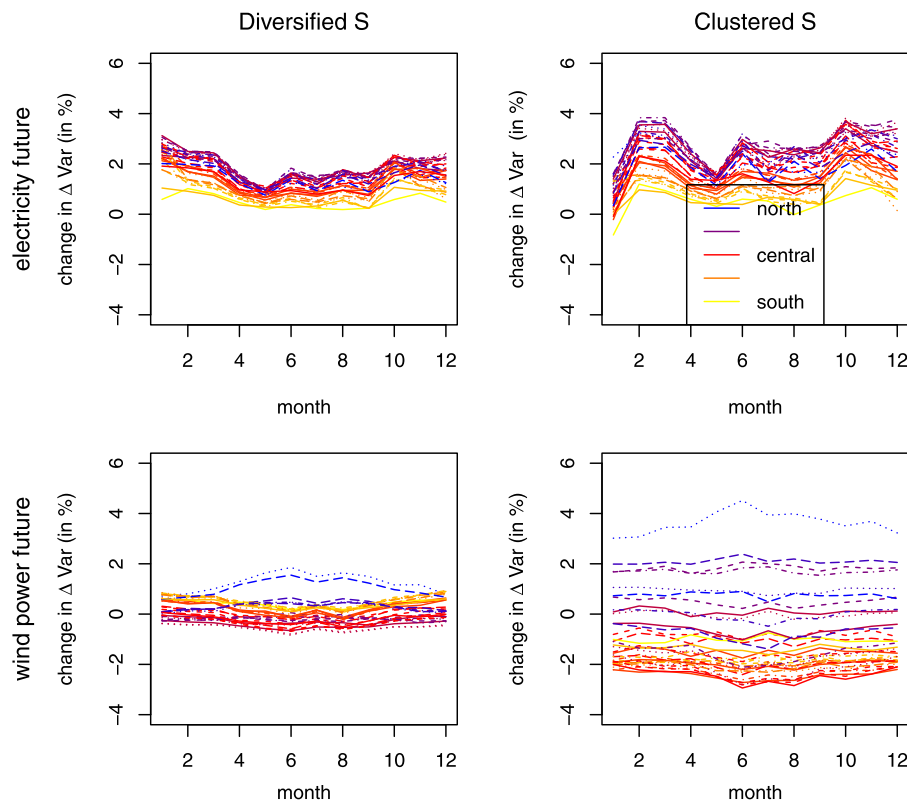
Fig. 11. **Impact on hedging efficiency due to capacity additions**. The figures give on overview of the differential impact of capacity additions on hedging efficiency and exhibit the differences from hedging efficiencies of two variants of new portfolio configurations and the base scenario. The top two figures correspond to electricity futures while the bottom ones correspond to wind power futures. The figures on the left side show the results for scenario Diversified S while the right hand side highlights scenario Clustered S.

Table 1
Renewable generation portfolio scenarios.

Scenario	Allocation criterion	Wind (GW)	PV (GW)
Base scenario	Spatial allocation based on Anlagenstammdatenregister, representing the renewable portfolio in Germany in 01/2013	31	36
Diversified S	(Yearly) Capacity additions according to BMWi (2016) equally distributed across all regions	34	37
Clustered S	(Yearly) Capacity additions according to BMWi (2016) clustered in high output regions	34	37
Diversified L	Capacity additions according to BMWi (2016) equally distributed across all regions (2025)	62	54
Clustered L	Capacity additions according to BMWi (2016) clustered in high output regions (2025)	62	54

pothetical extreme cases in which new capacities are either equally distributed ("Diversified S") or clustered in high output locations ("Clustered S"). This additionally allows us to grasp the role of the spatial distribution of newly installed renewable capacities. Table 1 gives an overview of these scenarios we seek to analyze along with the base scenario reflecting the current market environment used for the assessments further above. Fig. 10 shows the spatial distribution of the capacity additions in both scenarios for wind power. In order to quantify the impact of changes in hedging efficiencies for producers of renewable energy at different locations we reevaluate hedging effectiveness for each technology, location, and month separately and compare these values to the ones obtained under the base scenario. As the potential for risk transfer for the case of solar seems to be rather limited (e.g. see Section 4.3.1)

we mostly discuss results with regard to wind power in this section.

Fig. 11 summarizes the differential impact (ΔVar under the respective new scenario minus ΔVar in the base scenario) with positive values indicating a larger potential for risk reduction under the new scenario. Hedging efficiencies of the two derivative contracts react very differently to new capacity additions. For electricity futures, we find a consistently positive impact with efficiencies increasing slightly (up to almost 4%) for all locations irrespective whether the new wind power capacities are heavily clustered or equally distributed across the market area. The impact on wind power futures is different. Here, we find that for the diversified case of wind power capacity additions the average differences in hedging efficiencies are centered closely around zero. In contrast, the clustered case of new wind power capacities shows large dispersion across locations. Areas with new capacity additions exhibit larger increases in hedging efficiency (e.g. up to 4.5 percent for the

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additions are set to 2900 (730) MW while solar capacities are supposed to grow by 600 MW per year. For more details see BMWi (2016).

offshore location in the North Sea).[28] However, most onshore locations, especially southern ones, exhibit decreases in hedging efficiencies.

To understand these differences it is instructive to shed light on changes of dependencies between respective variables of interest. In the case of the electricity future, one obviously has to consider changes in the link between spot prices and (local) renewable production. Using simulations, we can verify that the price-quantity correlations are decreasing for all locations in both scenarios, that is, they become more negative. This can probably best be visualized by the notion of "systematic" wind risk. Intuitively, an increase in the overall wind power capacity raises the importance of wind power technology with regard to overall renewable power production.[29] And even if most new wind power is situated in specific regions only (as in our scenario Clustered S) there is a "common" component driving all wind speeds across the German market area. Although dependencies between wind speed in distant regions are generally lower ($\sim$30%) this "common" component is sufficient to raise dependencies between wholesale spot prices and wind power production at all locations. Overall, this explains why we see a consistently positive impact across all regions if the electricity future is considered as a hedging instrument.

In contrast, for the case of wind power futures a "redistribution" effect is driving the results. Changes in the efficiency of the hedge are mostly dictated by the relative contribution of each location to market-wide wind power production: Now, if most new capacity is situated in few locations, their relative contribution to market-wide wind power production will rise. Furthermore, more distant regions exhibiting lower dependencies to these candidates will then usually incur a drop in hedging efficiencies. This can be observed by comparing the two scenarios Diversified S and Clustered S. While for the former case, cross-sectional differences are rather minor[30], the latter case demonstrates how the regions in which new capacity is being located benefit in terms of hedging efficiency at the expense of more distant locations.

To give some quantitative insights on the long-term prospects of risk reduction through the use of financial derivatives we modify the generation portfolio according to plans made public throughout the EEG 2016. This results in two hypothetical portfolio configurations (Diversified L and Clustered L, Table 1) for the year 2025. Note that this implicitly requires us to assume that there are no changes in the characteristics of fundamental factors such as demand risk or the shape of the supply function which are arguably strong assumptions.[31]

Fig. 12 reveals that for the case of electricity futures, hedging efficiencies are likely going to rise considerably for the diversified case (Diversified L, top left figure) and even more so for the clustered case (Clustered L, top right figure). We find that in both scenarios variance reduction of the majority of locations rises by at least 15% . Note that on average hedging efficiencies across all regions are considerably larger for scenario Clustered L as more wind power is installed in the northern regions which are more windy. This results in larger overall wind generation levels compared to the more diversified scheme and a larger impact on wholesale electricity prices (more "systematic" wind risk in the system). Unsurprisingly, this causes a significant boost in hedging efficiency for electricity futures. In the long-run electricity futures thus seem to transform into more useful vehicles to mitigate uncertain production risks of wind power assets regardless of how the renewable generation portfolio changes.

As one would expect for the case of wind power futures, changes in the renewable portfolio configuration are going to have a smaller impact. With the exception of a single offshore location in the clustered configuration, changes in hedging efficiencies remain well below 10% and the more diversified expansion leads to a very low impact on ΔVar. Note however, that although hedging efficiencies for electricity futures might rise considerably in some instances on the long-run, they still remain below the values obtained from using wind power futures. Overall, these long-term prospects are qualitatively similar to those for the short-term. This means that the hedging efficiency of wind power futures is most likely not going to change significantly over time. Locations exhibiting a relatively low ΔVar (using wind power futures) at the current market state will therefore continue to suffer from a lack of effective hedging tools in the near future.

We undertake a similar analysis for the case of solar production. However, the potential for risk transfer remains at extremely low levels. In unreported results, we find that hedging efficiencies remain well below 0.5% (in variance units) for most of the year. This does not come unexpected as hedging efficiencies are already low for the base case (see Section 4.3.1) and new capacity additions are larger for wind power.

Overall, the analysis shows that changes in the portfolio composition of renewable assets can have a significant impact on hedging efficiencies but heavily depend on how the portfolio changes and which derivative product is being used for hedging purposes. Owners of renewable assets should therefore constantly keep track of developments in the distribution of installed capacities. Also, although electricity futures still offer rather poor capabilities in terms of risk reduction at current market conditions future prospects look much more positive.

5.2. Alternative subsidy mechanism

Next, we address the question of whether changes in the fixed price subsidy mechanism towards a more market-oriented approach result in significant increases in the riskiness of unhedged or hedged renewable portfolios. This should be especially interesting for investors considering the acquisition or construction of new physical renewable assets for which such an altered subsidy mechanism holds. One drawback of the fixed price subsidy mechanism is that the subsidy payments are very high and completely detached from current market conditions. That is, even if there is a temporary abundance of supply in the market and other market players are being paid less for the delivery of electricity, producers of renewable energy are still entitled to their fixed payments. Therefore, the producers' main concern is to maximize output, irrespective of market prices. Also, producers are not held responsible for large short-term deviations from expected generation levels out of their physical assets which have to be balanced by other flexible power plants.

To introduce a more market-oriented compensation scheme and foster investment into locations that produce relatively more in times of lower supply the previous legislation was changed in 2012

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[28] Since growth in offshore locations is bound to not exceed 730 MW, we assign this amount to one of the available offshore cells (North Sea) and allocate the rest to a closely located northern onshore location (see BMWi, 2016).

[29] Note that capacity is also increased for solar. However, compared to wind power its impact is much smaller.

[30] Changes within the diversified scenario are mostly attributable to cross-sectional differences in wind speed levels. The same unit of wind power delivers (on average) more power in northern more windy regions.

[31] Another simplification we use here is that renewable producers remain price-inelastic while recent changes in the subsidy mechanism introduce some dependence to wholesale prices. Under this altered mechanism there is some incentive to withdraw production volumes from the market in extreme cases, that is, when prices turn that negative that even the (relatively large) fixed subsidies cannot outweigh their impact on revenues. Since newly built capacity is compensated according to the altered scheme these extreme cases become more and more likely the larger the capacity additions become. We consider this altered scheme in more detailed in Section 5.2 but refrain from modeling such behavior completely as it would require us to modify the construction of the daily supply curve and leave this interesting aspect for future research.
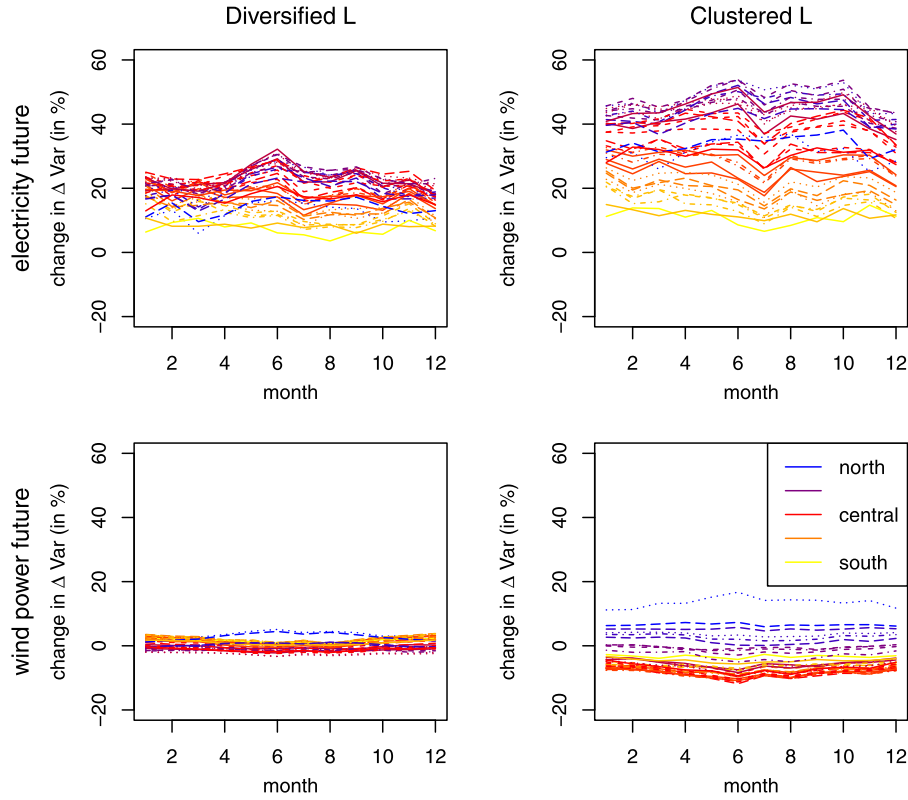
Fig. 12. Impact on hedging efficiencies for future scenario (2025). The figures give on overview of the differential impact of capacity additions on hedging efficiency and exhibit the differences of hedging efficiencies of two variants of a hypothetical portfolio configuration for 2025 and the base scenario. The top two figures correspond to electricity futures while the bottom ones correspond to wind power futures. The figures on the left side show the results for scenario Diversified L while the right hand side highlights the scenario Clustered L.

and 2014 to effectively force renewable generators to participate in the day-ahead market. Under the altered subsidy scheme the monthly revenue can be summarized as follows:

$$v_T^{u,k} = \sum_{t \in T} r_t^{u,k} F^u + \sum_{t \in T} r_t^{u,k} \left(s_t - \hat{s}_T^u \right). \tag{9}$$

In addition to the fixed subsidy payments (first summand in Eq. (9)) the monthly revenue is now additionally dictated by a second term that is linked to the (hourly) wholesale day-ahead spot prices s_t as well as a technology specific average market value in the respective month:

$$\hat{s}_T^u = \frac{\sum_{k \in K} \sum_{t \in T} \bar{r}_t^{u,k} s_t}{\sum_{k \in K} \sum_{t \in T} \bar{r}_t^{u,k}}. \tag{10}$$

where $\bar{r}_t^{u,k}$ corresponds to the overall renewable electricity production at location k of technology u (not to be confused with the generation from the specific producer $r_t^{u,k}$ above). The payments thus still entail fixed subsidy payments. However, the producer now additionally receives payments from selling his production on the wholesale day-ahead market ($\sum_{t \in T} r_t^{u,k} s_t$). To account for this additional revenue stream the regulator subtracts the average (technology-specific) market value resulting in the second summand in Eq. (9). Note that owners of physical assets built before 2012 are free to choose between the old or new scheme. Interestingly, the subsidy mechanism is applied for onshore and offshore wind assets separately. As a result, onshore and offshore assets are not directly "competing" against each other.

The scheme clearly favors generation from locations possessing more positive dependence to spot prices than their technology specific peers or in other words: it favors locations that are not perfectly correlated with the aggregated generation of the same technology. Consequently, an assessment of the risks associated with

revenues from wind parks or solar farms under the altered subsidy mechanism all the more requires an understanding of how local and market-wide generation as well as the wholesale spot prices interact. Ultimately, this is also reflected in the variance of the producers' revenues which now contains several additional terms:

$$\mathbb{Var}[v_T^{u,k}] = \mathbb{Var}\left[\sum_{t \in T} r_t^{u,k} F^u\right] + \mathbb{Var}\left[\sum_{t \in T} r_t^{u,k} s_t\right] + \mathbb{Var}\left[\sum_{t \in T} r_t^{u,k} \hat{s}_T^u\right] + \widehat{\mathbb{Cov}}$$

with $\widehat{\mathbb{Cov}}$ corresponding to the respective covariance terms:

$$\widehat{\mathbb{Cov}} = 2\mathbb{Cov}\left[\sum_{t \in T} r_t^{u,k} F^u, \sum_{t \in T} r_t^{u,k} s_t\right] - 2\mathbb{Cov}\left[\sum_{t \in T} r_t^{u,k} F^u, \sum_{t \in T} r_t^{u,k} \hat{s}_T^u\right]$$
$$- 2\mathbb{Cov}\left[\sum_{t \in T} r_t^{u,k} s_t, \sum_{t \in T} r_t^{u,k} \hat{s}_T^u\right]$$

Due to the different possible signs of the covariance terms it is not clear from the outset how much risk the altered mechanism introduces for the producer.[32] We therefore analyze each locations' unhedged and hedged revenue distribution and compare them to the results obtained for the fixed price subsidy mechanism.

We start our analysis by looking at potential peculiar differences of unhedged monthly revenue distributions (see top two graphs in Fig. 13). Interestingly, changes in the second moment

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[32] The intermittent nature of renewables makes an exact forecast of production levels often times impossible. The altered mechanism essentially requires producers to make forecasts and pay penalties for realized deviations (some more details given by German grid operators can be found at https://www.regelleistung.net/ext/static/rebab?lang=en). As a result, there are additional costs not considered here. For simplicity, we assume that the forecast error is independent from the location in question and neglect this part of the revenue in the following analysis.
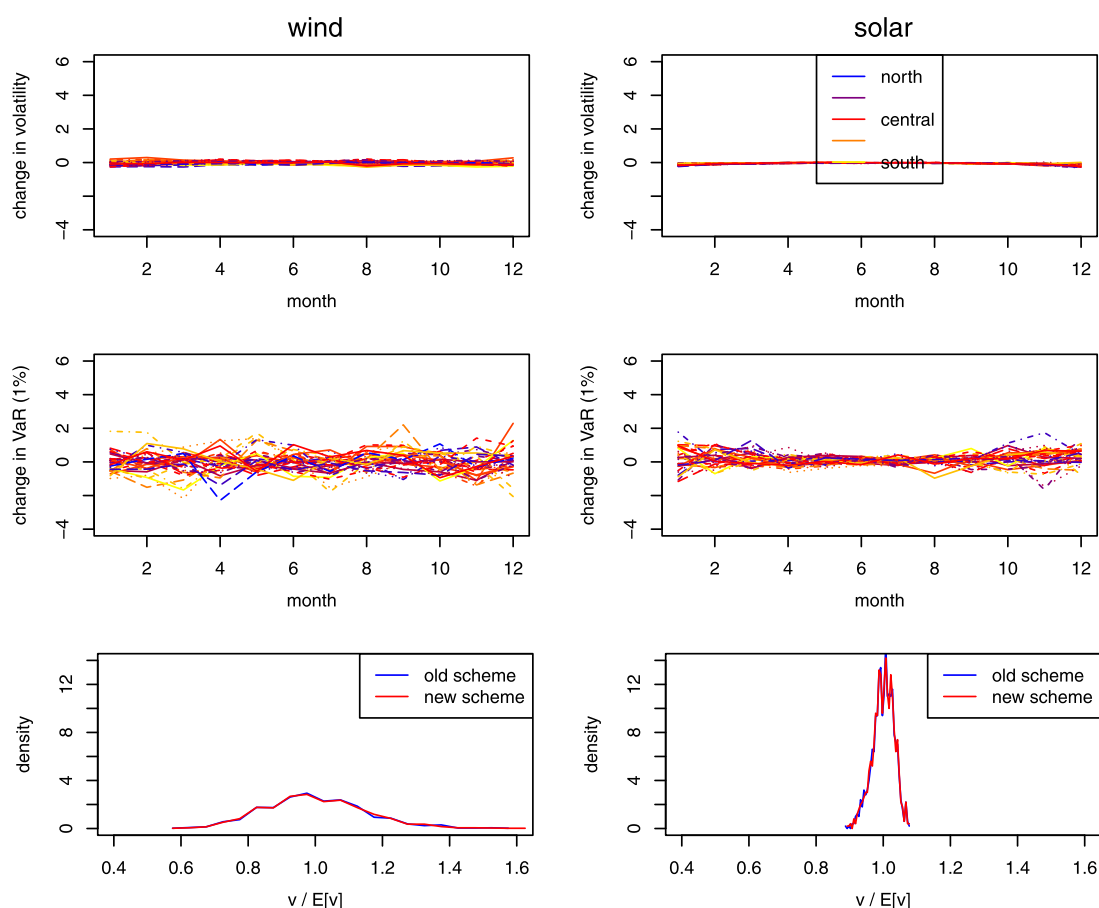
Fig. 13. Impact of market oriented subsidy mechanism. This figure summarizes the impact of the market oriented subsidy mechanism on revenue volatility (top tow graphs), VaR (middle two graphs), as well as the symmetry of the revenue distribution (bottom two graphs) for all months during a year. The bottom two graphs correspond to an exemplary location in the northwest of Germany for the month of July.

are hardly noticeable. Revenue volatility both for the case of wind power as well as for solar remains almost identical without showing any cross-sectional or seasonal patterns. The additional dependence to wholesale spot prices introduces additional uncertainties due to the presence of price spikes into the unhedged revenue distribution. Since volatility is not necessarily indicative for such tail risks we additionally have a closer look at 1% quantiles (VaR) as well. As Fig. 13 clearly shows these risk measures do not change by more than 1% in most cases. Furthermore, we do not find any significant changes in the symmetry of the revenue distribution with skewness and kurtosis remaining almost identical (e.g. see bottom two graphs of Fig. 13). We are also unable to spot any systematic bias in volatility or VaR when comparing northern and southern locations. These results suggest that the market component in the altered subsidy mechanism (Eq. (9)) has a much too small impact to have any significant effect on the riskiness of revenues of renewable producers at current market conditions. For robustness, we also experiment with lower levels of fixed subsidy payments F^u as this generally results in a larger weight for the spot price dependent terms in the monthly revenue. However, even for very low values (50 EUR / MWh) results remain very similar.

Although (unhedged) revenue distributions do not seem to be heavily affected it is still possible that the potential for risk transfer through financial derivatives changes. Yet, we also find that hedging efficiencies for electricity futures are hardly affected at all with ΔVar changing by less than 1% for both wind and solar, regardless of location or season. Results for wind power futures are similar. To set the results into perspective, we compare them with changes

induced by yearly alterations to the renewable generation portfolio in the last section. Ranging somewhere between 2–4% this demonstrates that developments in the generation portfolio seem to be far more important than additional risks introduced by the current market-oriented subsidy mechanism.

Our finding that the more market oriented subsidy mechanism does not change risk characteristics significantly appears to be linked to the large "systematic" component driving weather risks at all locations (as pointed out in Section 4.2). As a result, it appears intuitive that the additional term in (9) does not have a large impact on revenue uncertainty. The distribution of this additional term for every location can be found in Fig. 14. Locations are presented according to their y-coordinate, that is, the density for the most southern location can be found at the bottom (number 1). For simplicity, only the densities for the month of July are depicted, although other months look quite similar.[33] We start discussing the results for wind power (left column). It is clearly visible that the term's impact on revenue uncertainty is generally low. However, there is a tendency of southern locations to exhibit a slight positive bias whereas northern ones show a slight negative bias. Also, the densities appear more volatile for southern locations. Intuitively this makes sense: In cases when there is a lack of wind power production in the north, spot prices will be relatively high given the fact that most capacity is situated there as well. In such cases, southern locations can then often times sell their production

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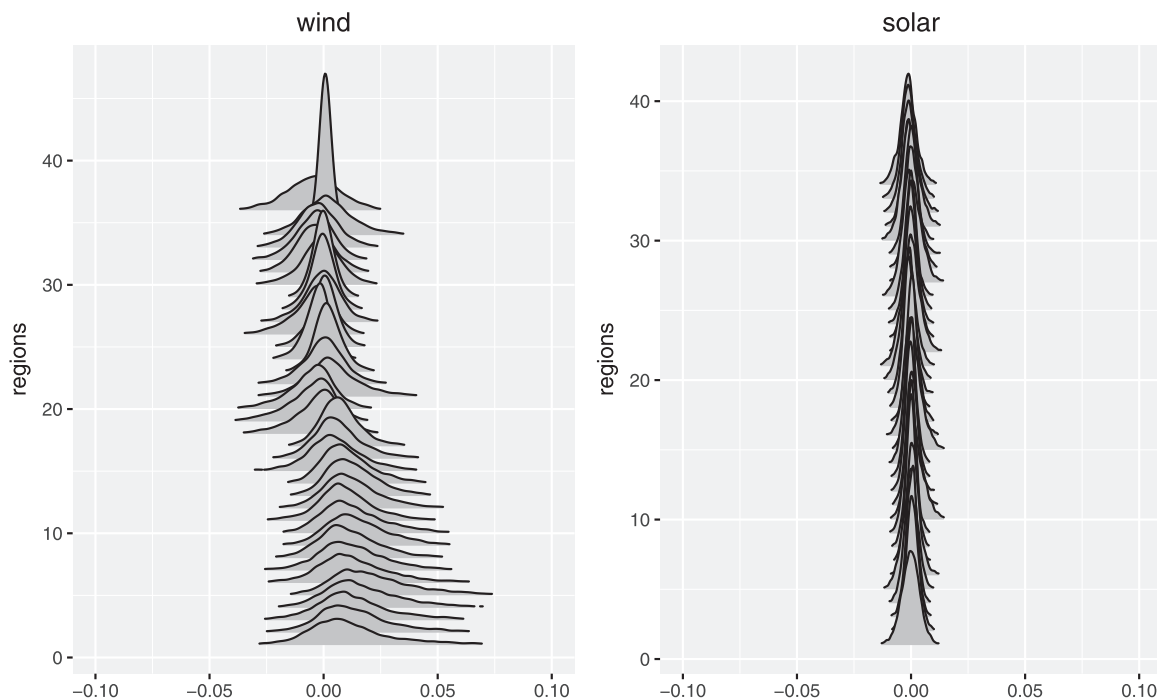[33] Data for other months is available upon request.

Fig. 14. Densities of additional subsidy-term. This figure shows the densities of the additional subsidy-term of (9) for wind (left) and solar (right) for all 38 locations in July. For convenience, the density has been normalized by the respective production level once again. Locations are sorted according to their y-coordinates, whereas the most southern ones are at the bottom (number 1 on y-axis).

for higher spot prices. Given there are much less wind power assets in the south, northern locations do not profit as much from an "idiosyncratic" drop of production volumes in the south which also explains why these densities are not as volatile as their southern peers. The relatively thin density for one of the very northern locations is an exception but can be explained by the fact that it corresponds to an offshore location whose additional subsidy term is independent from onshore locations. Also, and in accordance to earlier results, we are unable to find any discernable cross-sectional pattern of interest for solar. Here, the systematic component seems to be much more dominant.

Before we close the discussion on the new subsidy scheme, we want to take a brief view on the inherent optionality of renewable producers to turn off their production asset which we ignored so far (given the current very high subsidy level F^u). The new scheme actually introduces an incentive for producers to remove their production in times of excessively negative wholesale prices. For simplicity, assume the average market value of the asset's production $\hat{s}_T^u$ to be known ex-ante. Then, the producer will withdraw its quantities from the market whenever spot prices turn more negative than the asset's subsidy payments $F^u - \hat{s}_T^u$.[34] This will have multiple effects. First, the lower fixed subsidies become the more "'price volatility"-dampening the presence of renewables will get as they will render negative price spikes less likely. Second, risk characteristics of the revenue distribution might change, too. For instance, while for the old scheme weather systems with hours or even days of high wind speed lead to high (accumulated) payoffs for the producer, this is not necessarily the case for the new scheme anymore.[35] And third, dependencies between renew-

able production and other market variables, such as wholesale spot prices, will most likely change as well and with it will have an impact on hedging efficiencies of derivative products.

5.3. Hedging horizon

Both the time series of wind speed as well as solar irradiation are highly stationary. Pronounced mean reversion might therefore result in significantly lower production risks for longer time frames than months. We therefore enrich our initial assessment of unhedged renewable portfolios of Section 4.2 by looking at yearly revenue distributions. Fig. 15 depicts the various locations' revenue volatility (again, normalized by the respective expectation) for both technologies. Clearly, production risks appear to be much lower on this time frame. As can be seen, the volatility drops to roughly a third (fifth) of the monthly measure for wind (solar) (see Section 4.2, Fig. 5).

Could this yearly revenue uncertainty be hedged by means of yearly derivative contracts? As can be seen in Fig. 16, electricity futures remain poor choices for hedging production risks for both technologies. For the case of solar, the potential of variance reduction is non-existent on a yearly basis, much like for a monthly hedging window. Since dependencies between wind power and power prices drop during summer, it is not that surprising that the average (yearly) power contract performs poorly in terms of hedging efficiency as well. Wind power futures, on the other hand, remain potent tools to hedge production risks on a yearly time frame as well. This does not surprise too much since there is no large seasonal pattern in the hedging efficiency of wind power futures over the year, whereas for electricity futures there is.

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[34] In practice, $\hat{s}_T^u$ is unknown before the end of the month and would have to be approximated.

[35] Also note that after 4 hours of consecutive negative day-ahead prices the subsidies are actually cut under the new scheme (see https://www.gesetze-im-internet.de/eeg_2014/EEG_2017.pdf ,). Given such events are rather rare within our calibrated

model we ignored this aspect within our analysis. Nevertheless, this might become important if market conditions change considerably.
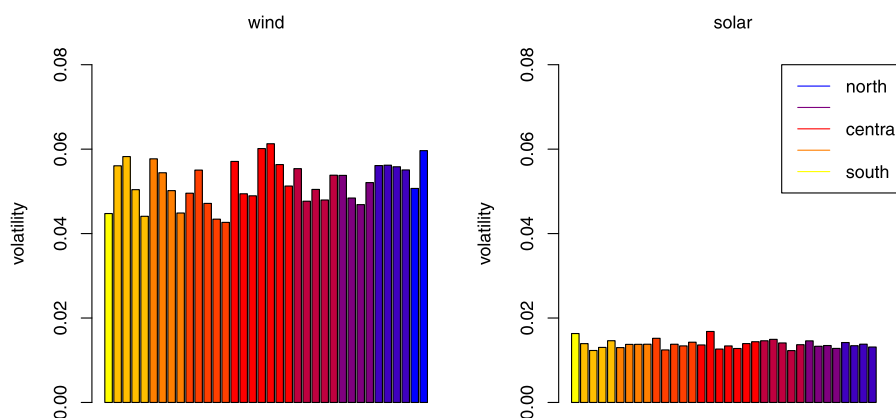
Fig. 15. Risk of unhedged revenues (yearly). This figure shows the volatility (normalized by its respective expectation) of the yearly unhedged revenues for wind (left) and solar (right).
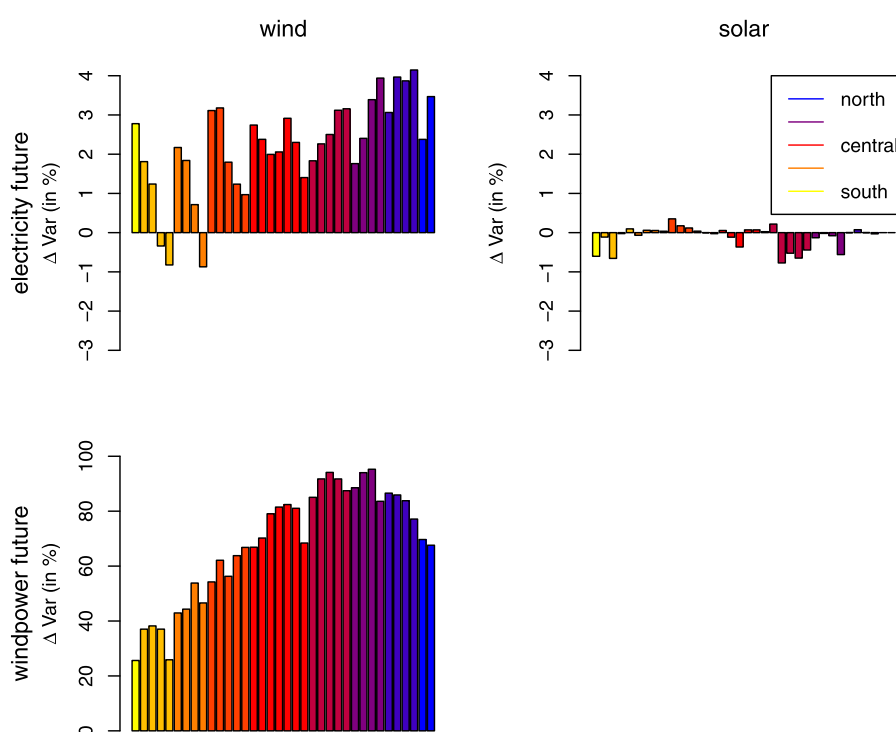

Fig. 16. Hedging efficiency of yearly revenues (yearly). This figure shows the hedging efficiency of yearly revenues for electricity futures (top) and wind power futures (bottom).

6. Conclusion and outlook

Facing uncertain production risk will inevitably become the new norm in many modern energy markets. In this study we gauge the potential for risk transfer through financial derivatives for such production risks in Germany, in which the presence of intermittent renewable generation is already felt quite significantly. Our results can thus serve as a first benchmark for developments in other countries contemplating the expansion of a carbon-free electricity sector. Since dependencies between local and global renewable generation as well as wholesale spot prices are necessary for such an assessment, we make use of a suitable hybrid structural electricity price model that captures the spatial distribution of renewable generation capacities.

We find that unhedged renewable energy portfolios are very risky compared to existing asset classes and that the risk trans-

fer by existing vanilla derivative contracts (electricity futures) is very ineffective, especially for the case of solar. There is some hope for the case of wind power though. First, a new exotic weather-related derivative instrument ("wind-power future") introduced by the EEX in late 2016 shows very promising results in terms of hedging efficiency (up to 95% for some locations). However, beside the fact that the contract lacks liquidity, its full potential is mostly limited to locations possessing a large amount of installed capacity. Consequently, exchanges contemplating new concepts of weather-related hedging instruments tailored to the need of their customers might want to take this aspect into consideration. Second, at least in the long-run hedging efficiency of electricity futures will rise considerably ($\approx$20–30%) due to the increasing role of wind power in the formation of wholesale spot prices. In the current market environment, however, it seems like renewable producers have to resort to customized contracts traded on OTC markets or to

reinsurance companies to transfer their location-specific revenue risks to third parties.

Our results furthermore underline the distinct role of the spatial distribution of the renewable generation portfolio. This distribution heavily dictates how effective hedging instruments work for different locations, seasons, and technologies. Furthermore, even short-term changes (1-year) can result in sizable impacts on the hedging performance. We also find that the more market-oriented subsidy mechanism introduced in 2014 does not result in economically significant changes in risk measures. Alterations to the renewable generation portfolio should thus be of much more concern for producers than changes introduced by the altered market mechanism.

We regard our analysis as a first step to foster the understanding of the dynamics in modern low-carbon economies. One could potentially look into alternative routes to hedge. As exchange-traded derivative instruments are limited in their potential or might not be an option for every type of investor, future studies could additionally look into the potential of (physical) hedges via spatial diversification of renewable capacites at different locations. Furthermore, once wind power derivatives markets mature it might also be insightful to quantify potential risk premia associated with transferring the (systemic) market price of wind power risk to other parties - providing valuable insights into the potential costs of following such hedging strategies.

Appendix A. Hybrid Structural Model Details

A1. Supply function f_t

The supply function f_t is specified as a time-dependent deterministic function as follows:

$$f_t(x) = \begin{cases} s^{\min}, & x \leq x_{\min} \\ \min\left(s_{\max}, \max\left(s_{\min}, c_t(x)\right)\right), & x \in (x_{\min}, x_{\max}) \\ s_{\max}, & x \geq x_{\max} \end{cases} .$$

$c_t(x)$ captures possible variations in the supply curve's shape during peak and offpeak hours:

$$c_t(x) = \begin{cases} \alpha_0 + \alpha_1 \frac{1}{(x - x_{\min})} + \alpha_2 \frac{1}{(x_{\max} - x)} + \alpha_3 x, & t \in T^{\text{peak}} \\ \beta_0 + \beta_1 \frac{1}{(x - x_{\min})} + \beta_2 \frac{1}{(x_{\max} - x)} + \beta_3 x, & t \in T^{\text{offpeak}} \end{cases}, \quad (11)$$

where T_{peak} and T_{offpeak} correspond to the set of time indices of peak and offpeak hours. Both the minimum and maximum wholesale price $s_{\min}$ and $s_{\max}$ as well as the minimum and maximum residual load values $x_{\min}$ and $x_{\max}$ are specified exogenously.[36] The second and third term in both equations of (11) essentially capture the non-linear behavior for very low and high levels of residual demand $\hat{d}_t$. This specification loosely follows Wagner (2014) but is different as such that spot prices are allowed to spike during both peak and offpeak hours.

A2. Production functions g_t^w and g_t^s

Given observed patterns regarding dependencies between renewable power production and its corresponding weather variable we choose a 3-parameter logistic function for wind and a second-order polynomial for solar:

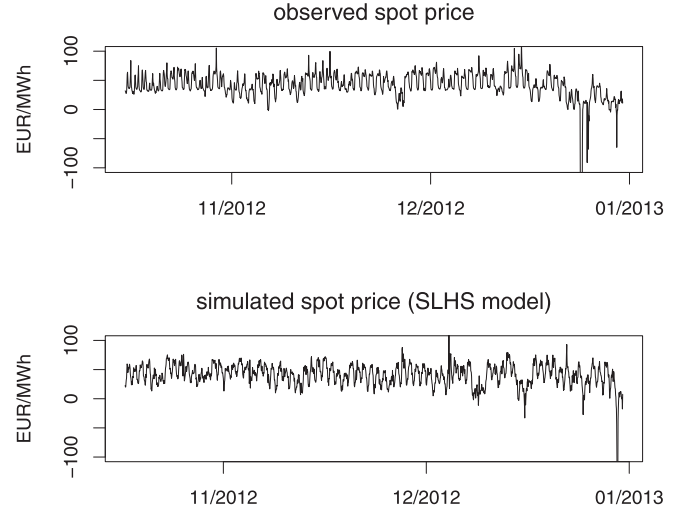$$g^{w,k}(y_t^{w,k}) = \frac{\gamma_0^k}{1 + e^{-\gamma_1^k(y_t^{w,k} - \gamma_2^k)}}$$

Fig. 17. Observed vs. simulated price trajectories The figure depicts observed (top) and simulated (bottom) day-ahead spot prices for late 2012.
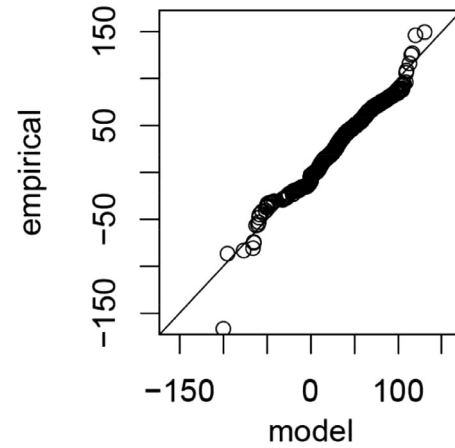

Fig. 18. QQ-plots between observed and simulated day-ahead prices The figure shows QQ-plots between observed and simulated spot prices using the reduced-form approach (top) as well as using the SLHS model (bottom).

$$g^{s,k}(y_t^{s,k}) = \pi_0^k + \pi_1^k y_t^{s,k} + \pi_2^k (y_t^{s,k})^2$$

Parameters are obtained by non-linear least squares (least-squares) for wind power (solar power).

A3. Goodness of fit

Since the model is being used to quantify risk exposures and deduce hedging strategies it is import that it has the capability to describe the system of relevant variables of interest realistically. We therefore quickly demonstrate its empirical fit to our underlying data set. Fig. 17 is an exemplary plot of the wholesale spot price s_t from October to December 2012, both empirical (top) as well as simulated (bottom). It can be seen that the stylized features of observed day-ahead prices seem to be captured quite well. For instance, negative price spikes tend to occur more frequently during winter holidays when the demand from large industrial consumers is missing. Fig. 18 depicts a QQ-plot of simulated vs. historical wholesale spot prices and demonstrates that the model is doing a good job at reproducing the shape of the empirical distribution. Last but not least, we show the model's capability to describe the joint distribution of the modeled (aggregate) drivers and wholesale spot prices - a property that can become very important for hedging practices. Table 2 depicts the time series correlations

Table 2
Correlations between spot prices and fundamental factors.

	Model	Data
ρ_{s_t, re_t^w}	−0.30	−0.37
ρ_{s_t, re_t^s}	−0.04	−0.04
ρ_{s_t, d_t}	0.65	0.66
$\rho_{s_t, \hat{d}_t}$	0.82	0.85

This table compares correlations of several fundamental factors (demand d_t, residual demand $\hat{d}_t$, wind generation re_t^w, as well as solar generation re_t^s) with wholesale spot prices s_t for the model (left column) as well as for the historical data (right column) during 2012–2014.

of renewable generation from solar, wind, demand, and residual demand with spot prices. As can be seen, the model-implied correlations are very close to what we actually observe.

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